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Research on wheelchair form design based on Kansei engineering and GWO-BP neural network

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With the increasing emphasis on humanistic care in society, consumers are no longer only concerned about the functional needs of products but also about the spiritual, cultural, and emotional needs that products bring to people. This study proposes a wheelchair form design method based on the Kansei engineering approach, which integrates the evaluation grid method (EGM), grey wolf optimization (GWO) algorithm, and back propagation neural network (BPNN) technology. The aim is to explore the connection between wheelchair form design elements and user emotions and help industrial designers find designs with emotional preferences. In this study method, firstly, the collected wheelchair samples were evaluated using the EGM, extracting upper-level Kansei vocabulary driven by user attractiveness, middle-level original attractiveness items, and lower-level specific design elements and extracting nine sets of Kansei vocabulary mentioned frequently by users. Meanwhile, the morphological analysis method is used to construct a sample library of product morphological elements. Secondly, the semantic difference and factor analysis methods were used to analyze the ratings of 9 pairs of Kansei words, and the weights of Kansei factors were calculated to identify three critical Kansei demand factors. Thirdly, based on the analysis results of the orthogonal experiment, a conceptual plan for the wheelchair was constructed using computer-aided technology Rhinoceros 3D modelling software. Fourthly, the semantic difference method is used to collect users' ratings of critical Kansei words for wheelchair concept schemes, and the evaluation values of critical Kansei words are calculated by weighting. Fifth, a BPNN based on the GWO algorithm will establish a predictive model between wheelchair design elements and vital Kansei images. Finally, the predictive performance of BPNN and GWO-BPNN models will be compared to verify their superiority. The results indicate that the GWO-BPNN model has better predictive ability and performance. The method proposed by this research institute can more effectively help industrial designers create products that meet users' emotional needs, providing a new perspective for wheelchair algorithm design.

Keywords Wheelchair design, Kansei engineering, Evaluation grid method, Grey Wolf optimization algorithm, Back propagation neural network

According to WHO data, approximately 75 million people worldwide must use wheelchairs[1]. For people who have difficulty or are unable to walk due to illness, injury, old age, or other reasons, wheelchairs are necessary personal mobility devices[2]. Wheelchair design has become essential to ensure that wheelchair products can meet users' material and emotional needs and improve their quality of life[1]. Whether wheelchairs can meet user needs is not only a key factor for manufacturers to compete for market share but also includes the satisfaction of functional and emotional needs[3]. Traditional enterprises pay more attention to the consumer needs of product structure and usage functions and less to whether the product's form, style, and emotional attributes match the consumer's needs[4]. However, visual appearance is one of the main factors influencing consumer purchasing decisions and stimulating emotions[5]. For wheelchair products, incorporating emotional design elements such as beautiful shapes can enhance users' confidence and help eliminate social prejudice against wheelchairs, promote social acceptance and respect for wheelchair users, and enable users to better integrate into society [6]. Therefore, in a market where emotional demands are increasingly growing, wheelchair manufacturers must attach great importance to the emotional needs of wheelchair users in their design and production processes[7]. However,

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capturing users' deep emotional appeals has always been a challenge for manufacturers, as these appeals are often elusive, and even users themselves may not be fully aware of their actual emotional needs[3,8].

Kansei Engineering (KE) is a technology that meets consumers' emotional needs and quantifies their emotional responses through engineering methods to support product design[9]. KE can help manufacturers identify user needs and obtain product feature combinations based on user preferences by studying the relationship between user needs and product features[3,5]. In recent years, the Evaluation Grid Method (EGM) has been successfully applied to KE to capture the attractiveness factors between consumers and product design elements[10]. For example, Ko et al.[11] explored the attractiveness factors of office chair products by combining EGM and Quantitative theory type 1 (QTT1) technologies. Chen and Li[12] obtained specific features of game design based on EGM and used multiple linear regression (MLR) analysis to explore different players' views on the design. Therefore, this study integrates KE and EGM to collect and analyze consumers' emotional descriptions and evaluation of products to obtain users' emotional needs data. According to these methods, designers can define the emotional goals that must be met in product design, such as consumers' expectations for product appearance, functionality, and user experience, to match consumers' emotional needs with product design elements and generate product concepts with significant emotional features.

In the generation stage of product concepts, designers need to collect existing product images for reference and express design concepts in the form of 2D sketches or 3D models[13,14]. Usually, 2D drawing is superior to 3D modelling in speed and convenience[15]. In the early stages of product design, 2D shapes and contours are used to visualize design ideas and concepts[13]. 3D models, such as showcasing case studies and detailed designs, are more commonly used in the later stages of product structure establishment. At these stages, the 3D shape contour provides a source of information about the three-dimensional structure of the object, namely the preliminary product layout[16]. However, in current product design evaluations, the analysis of semantic differences in products often relies on finished product images rather than natural objects, conceptual representations, or interactive interfaces[17]. This approach limits the comprehensive understanding of product form and the possibility of influencing design during product ideation[13]. Wang and Zhou[7], as well as Yang et al.[3], pointed out in their research that products displayed solely through 2D floor plans lack a sense of three-dimensionality and cannot truly reflect the three-dimensional visual characteristics of the product. To give users a more comprehensive understanding and perception of the product's form[18]. Cok et al.[13] studied the impact of 2D and 3D shapes on user perception and found that shape contours can serve as an information source for perceiving the 3D shape structure of objects. Tavanti and Lind[19] studied the effects of 2D and 3D displays on user spatial memory. Their research reveals the positive impact of three-dimensional representation of information on users. In the field of product design, the 3D form of a product can better stimulate individual emotional responses[20]. The form of a solid is one of the fundamental elements of three dimensions[13]. Therefore, this study uses 3D modelling techniques to generate the 3D shape to be studied from 2D shapes. Moreover, a conceptual plan for the product must be established based on the product's structure. These 3D conceptual models represent samples for evaluating essential Kansei requirements in the fifth stage. Using 3D conceptual models instead of images as evaluation objects enriches the dimensions of design evaluation and provides users with a more intuitive and realistic evaluation experience, which helps to more accurately capture and reflect users' emotional needs and preferences in the early stages of product design.

With the development of artificial intelligence technology, various techniques have been introduced to quantify the concept of KE. These techniques include Grey Relational Analysis (GRA), Neural Networks (NN), Support Vector Machines (SVR), Fuzzy Logic, Linear Regression, Rough Set Theory (RST), Quality Function Deployment (QFD), and Theory of Inventive Problem Solving (TRIZ)[10,21–23]. These methods quantify the impact of different design elements on emotional responses through the coefficients of independent variables to facilitate the identification of key design elements[24]. It helps establish a correlation model between design elements and consumer perception, accurately grasp product design direction, and improve design efficiency[24]. In the research methods of KE, three-layer back propagation neural networks (BPNN) are widely used to establish the relationship between styling design elements and consumer image perception[21]. For example, Chen[25] used BPNN to establish a mapping model between the emotional intentions of middle-aged and elderly users and critical design features of human–computer interfaces. Liu et al.[26] extended the mapping model between smartphone product parameters and Kansei evaluation values using BPNN. Wu et al.[27] used computer mouse design as an example. They constructed a Kansei model between design elements and Kansei imagery through NN, providing a new design method that caters to users' emotional needs[28]. However, BPNN is a "black box" model, and it is tough to train the model and explain its parameters based on a deep understanding of the data used in model construction exercises[28]. Although BPNN has a simple structure and nonlinear solid fitting ability, it also has some limitations, such as low generalization ability, slow convergence speed, overfitting, and the tendency to fall into local optima problems[28,29].

Regarding the limitations of BPNN, many researchers have explored various methods to optimize it, such as widely used genetic algorithm (GA), artificial bee colony algorithm (ABC), particle swarm optimization (PSO)[7,30,31]. Wu[32] introduced the Non-Dominated Sorting Genetic Algorithm II algorithm into BPNN to derive the Pareto optimal form design for electric motorcycle products. Liu et al.[31] used ABC to optimize the initial weights and biases of BPNN to improve the accuracy and convergence speed of predicting emotional semantics in human–computer interaction interfaces while preventing the learning algorithm from falling into local optima. In recent years, many scholars have been inspired by the collective intelligence and foraging of natural organisms and have proposed many intelligent bionic algorithms. For example, Abdollahzadeh et al.[33] was inspired by the lifestyle of African vultures and proposed the African Vulture Optimization Algorithm to simulate their foraging and navigation behaviour. Mirjalili et al.[34] proposed the Grey Wolf Optimizer (GWO) algorithm based on the hunting behaviour of grey wolves. Research has shown that the GWO algorithm exhibits significant advantages in optimizing BPNN due to its simple structure, high predictive ability, and fast convergence to the optimal solution, which can save a lot of time and effort. For example, Uzlu[35] used the GWO algorithm to optimize artificial neural network (ANN) for predicting greenhouse gas emissions and compared it with ANN-BP, ANN-ABC, and ANN-TLBO (teaching learning-based optimization) models. The results showed that GWO-ANN had better stability and prediction performance. Therefore, this study utilized the advantages of the GWO algorithm to optimize BPNN and constructed a mapping model between wheelchair form design elements and user Kansei needs. By comparing with traditional BPNN prediction models, the model's superiority is verified. This study aims to select a prediction model with higher performance that can more accurately capture users' emotional needs, guide product design, and improve scientific and practical design.

The rest of this article is organized as follows. In Sect. 2, we reviewed this study's theoretical and methodological background, providing its theoretical support. Section 3 provides a detailed introduction to this study's methodological framework, process, and descriptions of each stage. To demonstrate the application process and effectiveness of the method through empirical research on wheelchair design cases. Section 4 conducted in-depth discussions based on the research results and explored the reliability of the prediction model. Finally, in Sect. 5, we summarized the main contributions of this study and pointed out its limitations and future research directions.

Related work

Traditional wheelchair design methods mainly emphasize the product's functional attributes while easily ignoring emotional needs. Therefore, this article uses EGM to evaluate the collected wheelchair samples, extracting upper-level sensory vocabulary driven by user attraction, middle-level primitive attraction items, and lower-level specific design elements. In addition, based on the KE method combined with GWO and BPNN, the aim is to explore the intrinsic connection between wheelchair form design elements and user emotional needs to create product designs that meet user emotional needs. To achieve this goal, this chapter provides an overview of the research progress in wheelchair design, KE, EGM, and GWO-based BPNN to promote their application in innovative product design.

Wheelchair design

Wheelchairs are essential mobility tools to assist groups who cannot walk independently in social activitie[2]. To enable wheelchair users to live independently, wheelchair design is crucial for both users and manufacturers. At present, research on wheelchair design mainly focuses on the improvement and optimization of various structural functions, the operability of shapes, and the potential health risks associated with using wheelchairs. For example, Hein et al.[36] studied the use of folding frames to improve an ergonomic manual wheelchair, which can reduce weight and increase accessibility. Misch et al.[37] studied the effects of wheels and casters on vibration attenuation and propulsion costs of manual wheelchairs. Harbert[38] has developed versatile wheel technology to design wheelchairs with excellent maneuverability and smaller turning radii. Chiba Technology has created a four-wheel robot wheelchair that can turn wheels into legs, allowing for climbing stairs[39]. In addition, MIT has developed an affordable all-terrain wheelchair that can adapt to diverse usage scenarios[40]. In addition to studying the wheels, researchers have also studied other structures of wheelchairs. Koyama et al.[41] investigated the impact of differences in the shape of the joystick of a wheelchair on subjective and objective operability. Comellas et al.[42] developed a new type of armrest to meet the demand for increased arm exercise and living ability after treating stroke. Sonenblum et al.[43] evaluated the effect of different wheelchair cushion designs on buttock tissue deformation. Damiao et al.[44] studied shape-capture methods to create customized contour wheelchair cushions to reduce the risk of pressure injuries. However, many studies have improved and developed new wheelchairs from the perspective of performance and appearance to meet different users' material and functional needs. With the increasing emphasis on humanistic care and spiritual emotions in society, designers are paying more and more attention to consumers' psychological feelings beyond functionality[45]. The shape of the product is an essential factor. The appearance of a product seriously affects consumers' preferences and choices for the product[24]. Different product forms can create different feelings for customers, who often choose products that meet their psychological expectations[46]. Emotional and personalized wheelchair design can not only enhance the confidence of wheelchair users but also help eliminate social prejudice against wheelchairs and promote social acceptance and respect for wheelchair users. Therefore, manufacturers and designers must design a wheelchair product that can meet the emotional needs of users.

Kansei engineering (KE)

KE is an innovative technology initially proposed by Kenichi Yamamoto, Chairman of Mazda Motor Company in Japan, in 1986 and further developed and practised by Japanese scholars such as Mitsuo Nagamachi, and Yohei Harada[3,9,47]. The core of KE lies in analyzing and quantifying consumers' psychological feelings towards products, transforming these subjective Kansei needs into specific design parameters to design products that better meet consumers' expectations and needs[23,48]. The primary task of KE is to accurately capture customers' psychological expectations, as this is directly related to the product's market success. KE's initial work typically involves evaluating product characteristics through ergonomic and psychological methods. If positioning customers' emotional needs is inaccurate, it may lead to product development failure and bring considerable risks to the enterprise. To solve this problem, researchers measure users' emotional reactions to the product after obtaining their needs, establish the relationship between needs and product characteristics, and guide product form design[3].

Initially, KE research quantified user emotions using the Likert scale or semantic difference (SD) method to evaluate users' emotional responses to products[49]. Later, researchers began to use mathematical methods to analyze the quantitative relationship between user emotions and product characteristics, such as using linear methods such as QTT1 and MLR to establish mapping relationships[50]. Some studies have introduced machine learning algorithms such as NN and SVR into KE's research to construct mapping models[51]. In addition, some studies utilize big data and artificial intelligence technologies to build systems that provide design solutions for users, which simulate and optimize the design process through computer systems[47]. Much research combining KE and these methods has been widely applied in various design fields. For example, Lin et al.[52] conducted perceptual semantic experiments on Ming style, Qing style, and modern Chinese furniture using KE. They established a mapping model between the morphological elements and emotional responses of solid wood seats using QTT1 and MLR models. Chen and Cheng[53] established a correlation model between clothing pattern design elements and young people's emotional imagery through QTT1 to solve the mismatch problem between personalized consumer needs and clothing pattern design. Lin et al.[21] established a predictive model between the overall design elements of electric shavers and user Kansei evaluation based on QTT1, combined with BPNN and GA-based BPNN. Zhang et al.[54] proposed a preference-based auxiliary product design model (PAPDM) by combining various methods such as KE, EGM, QTT1, universal design, TRIZ, finite structure method, morphological diagram, and analytic hierarchy process (AHP). The PAPDM framework provides designers a transparent and progressive approach to designing assistive products that meet older adults' unique needs and preferences. Chen[25] used KE, RST, and BPNN to establish a mapping model between the emotional intentions of middle-aged and elderly users and critical design features of human–computer interfaces, and designed human–computer interfaces that can meet the emotional needs of middle-aged and elderly users. Lee and Han[5] combined technologies, such as the Kawakida Jirou method, GRA, and QTT1, with users' emotional needs to develop a practical, emotional soccer shoe recommendation system. Chen and Chen[55] used GWO-BPNN and KE to establish a mapping model between consumer perception and design elements of Paper-cutting patterns in Zhangpu to predict consumers' perception of Paper-cutting patterns. Therefore, KE can be integrated into digital technologies to obtain consumer feedback and valuable design information. However, although this comprehensive KE recommendation system has been widely applied in different product designs, it is rarely used in the form design of wheelchairs.

Evaluation grid method (EGM)

Miryoku Engineering, as a branch of KE, focuses on exploring user preferences and identifying product attractiveness factors through EGM and expert interviews[47]. Attraction refers to the positive factors that make a product attractive, carrying the needs of users for various aspects of the product[56]. By utilizing the principles and methods of Miryoku Engineering, it is possible to effectively discover and evaluate the attractiveness of wheelchair shapes, accurately capture users' perceptual images, and provide positive references for shape designers[7]. In general, the attractiveness factor of a product can be obtained through EGM. EGM is an effective Miryoku Engineering research method proposed by Japanese scholar Junichiro Sanui[57] after studying the knowledge base grid method of psychologist George Kelly[58]. Another improvement is to use the primary problem method of stairs proposed by Sinkel in 1965[59], which can lead to higher-level constructions related to the initial expression at a lower level. The EGM method mainly uses personal interviews to discuss the similarities and differences between subjects A and B through paired comparisons to sort out the individual qualities of the target subject[57]. The specific steps include: firstly, comparing the objects to be evaluated. Require participants to answer what they are satisfied or dissatisfied with and what they like or dislike[7]. Secondly, clarify the meaning or conditions through supplementary questions based on their answers[47]. Then, through EGM, a three-layer relationship logic diagram of product attractiveness factors can be obtained, including the upper layer (Kansei words), middle layer (original evaluation layer), and lower layer (specific design elements)[7]. Translate users' emotional preferences into specific product design parameters, provide visual design suggestions for designers and related developers, and maximize user satisfaction with the product.

Due to its high performance in extracting attractive factors, EGM has been widely applied in product design. For example, Wu et al.[60] used EGM to analyze the attractiveness factors of existing cure products during COVID-19. They proposed practical cure product design strategies to help develop and evaluate treatment products and alleviate people's anxiety during the pandemic. Zhang and Li[61] used EGM to extract the attractiveness factors of green products and analyzed the influence weights of green product design factors using QTT1. Kang[62] used EGM to establish a three-level evaluation grid platform and used NN to establish a mapping function between key Kansei factors and representative product design elements, discovering the most aesthetically pleasing product designs. Wang and Zhou[7] applied EGM to establish key attraction factors for electric bicycle products and completed innovative design and development of product forms. Liu et al.[63] used EGM to collect and analyze customer requirements and design elements, calculated the weight values of customer requirements using AHP, and finally established a fuzzy relationship matrix through QFD to explore design elements based on user requirements.

Back propagation neural network (BPNN)

In Kansei engineering, BPNN is widely used to determine the mapping relationship between product design elements and consumer emotional responses and to make emotional predictions. BPNN is a multi-layer feedforward artificial neural network training based on the error backpropagation algorithm proposed by Rumelhart and McClelland[25]. It conducts data simulation training through a three-layer structure model of the input layer, hidden layer, and output layer, simulating the learning process of a human NN to establish a nonlinear mapping relationship between user emotional needs and product design elements[25]. Specifically, the input layer is used to input feature information of product design elements, the output layer is used to display user Kansei evaluation results, and the hidden layer is used for non-linear processing of data relationships. Related studies have elucidated the application of BPNN in the field of product design. For example, Gao[64] used BPNN to analyze users' expectations for watch styling and established a predictive model between design elements and emotional responses, providing better design references and indicators for innovative watch styling design. Guo et al.[65] established a BPNN model to analyze the relationship between mobile phone design variables and user preferences in order to optimize mobile phone design. Chen and Cheng[66] constructed a mapping relationship between user perception and pattern design elements through BPNN, providing a more scientific and intelligent pattern design method. Chen[25] used BPNN to build the mapping relationship between the perceptual image of middle-aged and elderly users and the design features of the human–machine interface of the auto drive system and designed a human–machine interface that can meet the perceptual needs of middle-aged and elderly users. Fan et al.[67] applied KE and BPNN methods to explore consumers' preferences for 3D printing cloud service platforms. Misaka and Aoyama[68] developed a cup crack pattern design system based on KE using NN. Therefore, BPNN is able to learn and simulate the complex emotions and emotional responses involved in the Kansei project. By training neural networks to recognize and simulate these responses, we can better understand consumer needs and design products that better meet user expectations.

Grey wolf optimization-based back propagation neural network (GWO-BPNN)

ANN models are a typical method in nonlinear regression analysis[69]. BPNN has been widely used in product optimization design because it can learn and store many input and output mapping relationships[69]. However, although BPNN has a simple structure and nonlinear solid fitting ability, it also has some limitations, such as low generalization ability, slow convergence speed, overfitting, and the tendency to fall into local optima problems[29].

GWO is a simple and robust metaheuristic algorithm that can solve constrained or unconstrained optimization problems. Although the GWO algorithm is relatively new, it has already been applied in various fields, such as environmental engineering, industrial engineering, and industrial design[35,55,70]. Some comparative studies have shown that the performance of the GWO algorithm is superior to other advanced optimization techniques such as PSO, GA, and Ant Colony Optimization (ACO)[34,71]. For example, Uzlu[35] introduced GWO into ANN to develop the ANN-GWO model for estimating future greenhouse gas emissions and compared it with ANN-BP, ANN-ABC, and ANN-TLBO models. The results indicate that the ANN-GWO model better predicts greenhouse gas emission levels. Hadavandi et al.[70] introduced GWO into neural networks and combined it with response surface methodology to model the strength of spinning yarn in spinning mills. Chen and Cheng[55] used GWO and BPNN to establish a prediction model to make a perceptual evaluation of Zhangpu Paper Cuttings patterns and compared it with the BPNN and FA-BPNN models. The results indicate that although the convergence speed of the GWO-BPNN model is slightly lower than that of the FA-BPNN model, its prediction accuracy is significantly better than other algorithms. Based on the above research, GWO can effectively optimize the weights and structure of BPNN, thereby improving its generalization ability, accelerating convergence speed, and reducing the risk of overfitting and falling into local optima. By integrating GWO and BPNN, a better-performing hybrid model can be constructed to meet higher accuracy prediction requirements. Although BPNN has a simple structure and nonlinear solid fitting ability, it also has some limitations, such as low generalization ability, slow convergence speed, overfitting, and the tendency to fall into local optima problems.

The development of the GWO algorithm was inspired by the natural foraging behaviour of wild grey wolves and their social hierarchy[72]. In GWO, the solution is simulated as the location of wolf prey, and the algorithm searches for the optimal solution by simulating the social hierarchy and foraging behaviour of grey wolves. As shown in Fig. 1, there are four types of wolves in GWO to simulate this leadership hierarchy: alpha (α), beta (β), delta (δ), and omega (ω)[34]. The alpha wolf is the leader wolf, responsible for making decisions and giving orders to the wolf pack. Beta wolves are subordinate wolves that assist alpha wolves in making decisions or organizing population activities. The δ wolves are reconnaissance, guard, old, and predatory wolves. They must obey the α and β wolves, but they dominate the ω wolves. Wolves are considered the bottom of the pack, often sacrificing themselves to other levels of wolves while foraging and protecting their territory. By simulating this social structure and behaviour pattern, the GWO algorithm can effectively search for the optimal solution in the solution space. It has demonstrated its efficiency and robustness in multiple optimization problems[35,55].

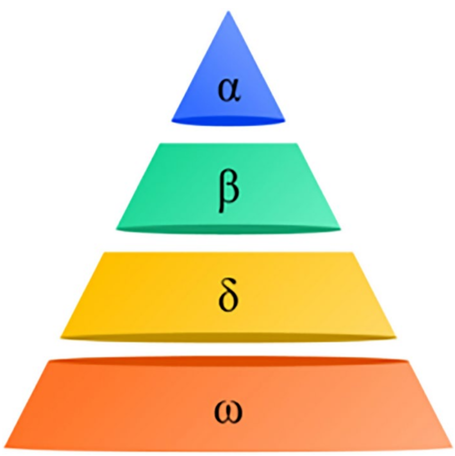


Fig. 1. Grading of Grey Wolves.

Establish a mathematical model for the GWO algorithm. α, β, and δ represent the optimal solutions in the current solution set, namely the first, second, and third optimal solutions[34]. These solution sets represent the leaders in the wolf pack, while the remaining candidate solutions are classified as ω, representing other group members. In this study, the solution is to optimize the weight parameters of BPNN. Wolves hunt (i.e., optimize) under α, β, and δ guidance. The mathematical model is as follows:

During the optimization process, the wolf pack updates their position according to Eqs. (1) and (2), simulating the behaviour of grey wolves gradually approaching and surrounding their prey[71]:

$$D(t) = |C \cdot X_P(t) - X(t)| \tag{1}$$

$$X(t+1) = X_P(t) - A \cdot D(t) \tag{2}$$

Among them, X (t) represents the position vector of the grey wolf, $X(t+1)$ represents the new position vector of the grey wolf, t is the current iteration count, $\mathrm{X_P}$ indicates the location of prey, and D (t) represents the distance between the grey wolf and its prey.

Furthermore, A and C are two collaborative coefficient vectors calculated using Eqs. (3) and (4).

$$A = 2a \cdot r_1 - a \tag{3}$$

$$C = 2r_2 \tag{4}$$

Among them, $\mathrm{r_1}$ and $\mathrm{r_2}$ are random numbers uniformly distributed between 0 and 1. The convergence factor a is a key parameter that balances the exploration and development capabilities of GWO. During the optimization process, the value of a decreases linearly from 2 to 0 as the number of iterations increases. Each wolf can change its position to a random location around its prey according to Eq. (4). When $|A|< 1$, wolves must attack their prey (i.e., find a new solution near the given one); When $|A|> 1$, the wolf turns to other prey (i.e., a better solution). Vector A allows the GWO algorithm to search for all points in the solution space[35]. When encountering problems such as getting stuck in local minima or memory ($|C|> 1$), vector C provides random values to search for new prey, just like wolves in nature search for new prey instead of taking risks and wasting energy on highly challenging/potentially failed hunting.

In nature, although α wolves usually guide hunting, other levels of wolves cooperate to surround, chase, and attack prey. However, in the process of evolutionary computation, the position of prey (optimal solution) is unknown. Therefore, in the GWO algorithm, the optimal gray wolf is considered α, the second-best gray wolf is considered β, the third-best gray wolf is considered δ, and the rest of the gray wolves are considered ω. The α wolf represents the candidate solution closest to the optimal solution, and the characteristic that β and δ have more knowledge about the position of prey is established in the model. During the iteration process, α, β, and δ are used to guide the movement of ω, thereby achieving global optimization[34,71]. Using the positions X_α, X_β, X_δ of α, β, δ, update the positions of all gray wolves using Eqs. (5–11):

$$D_\alpha(t) = |C_1 \cdot X_\alpha(t) - X(t)| \tag{5}$$

$$D_\beta(t) = |C_2 \cdot X_\beta(t) - X(t)| \tag{6}$$

$$D_\delta(t) = |C_3 \cdot X_\delta(t) - X(t)| \tag{7}$$

Among them, D_α, D_β, and D_δ are the distances between individual gray wolves ω and the α, β, and δ wolves, respectively.

$$X_1(t) = X_\alpha(t) - A_1 \cdot D_\alpha(t) \tag{8}$$

$$X_2(t) = X_\beta(t) - A_2 \cdot D_\beta(t) \tag{9}$$

$$X_3(t) = X_\delta(t) - A_3 \cdot D_\delta(t) \tag{10}$$

$$X(t+1) = [X_1(t) + X_2(t) + X_3(t)]/3 \tag{11}$$

Among them, X_1, X_2, and X_3 represent the positions that the individual ω gray wolf needs to adjust due to the influence of α, β, and δ wolves, respectively. A_1, A_2, A_3 and C_1, C_2, C_3 are coefficient vectors of α, β, and δ wolf motion. Figure 2 shows the process of updating patterns of α, β, δ, and ω wolves. There is one ω wolf in Fig. 2, but there could be more. Based on the distance between the wolf and its prey, the wolf can update its position using Eqs. (1) and (2). The obtained solutions are sorted from best to worst in terms of prey quality. The first three best solutions are considered α, β, and δ, respectively. Then, other wolves in the population are considered as ω and repositioned based on α, β, and δ. The proposed mathematical expression for repositioning the ω wolf is shown in Eq. (11).

In this way, the GWO algorithm simulates the collective hunting behaviour of grey wolves in natural environments, approaching the optimal solution by continuously updating the position of the wolf pack. This method has demonstrated efficiency and robustness in solving complex optimization problems, especially in applications such as BPNN weight optimization. Taking advantage of the fast convergence and powerful global search capability of the GWO algorithm, the weights and thresholds of BPNN are treated as the location information of grey wolves, and the ability of grey wolves to search for prey is utilized to update the location information, that is, to update the weights and thresholds of wolves[55].

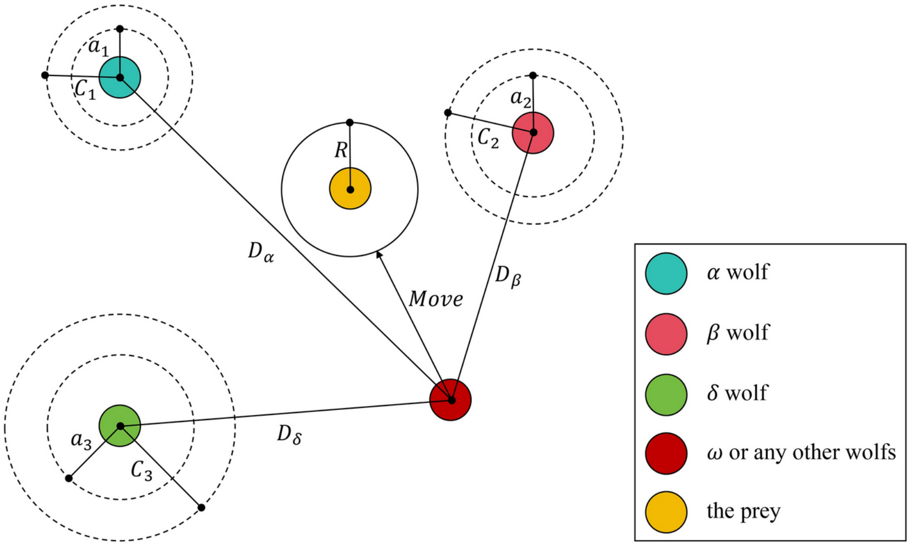


Fig. 2. Updating the location of Grey Wolves.

Methods

This study uses the KE method and EGM and GWO-BPNN technology to conduct a comprehensive quantitative and qualitative analysis of wheelchair shape design. The research process is shown in Fig. 3, divided into the following stages: Phase 1: Extracting the original attraction items of the wheelchair shape through EGM, the abstract emotions of the upper layer, and the design items of the lower layer. Phase 2: Based on the results of EGM, extract users' Kansei needs and deconstruct wheelchair form design projects and design categories using the form analysis method. Phase 3: Using Rhinoceros 3D modelling software, convert the categories of design elements in 2D form into 3D shapes and construct a preliminary product plan of a 3D conceptual model as the evaluation object for the next stage (wheelchair concept plan). Phase 4: Use FA to calculate the weights of Kansei factors and identify key Kansei demand factors. Conduct a critical Kansei words evaluation of the wheelchair representative scheme. Then, essential Kansei demand evaluation and prediction models based on BPNN and GWO-BPNN will be established, respectively. Finally, compare and analyze the results of these two prediction models to verify their effectiveness and feasibility. The experimental procedures were approved by the Bioethics Committee of the East China University of Science and Technology, and all methods were performed in accordance with the relevant guidelines and regulations. All participants gave their informed consent.

Identification of attractive factors

In this study, EGM was used to identify attractiveness factors. The specific steps are as follows:

Step 1: Collect and screen representative samples. Through various channels such as online shopping platforms, official websites of wheelchair brands, Design website, and consulting magazines and books, 234 wheelchair product sample images were collected. After screening the collected images to remove pixel blur and images with similar shapes, 35 representative wheelchair samples were finally selected, as shown in Fig. 4. For the uniformity and comparability of the experiment, the chosen representative sample images were processed using PS software into uniform-sized 25 cm × 25 cm images and decolourized as materials for the EGM interview experiment to facilitate subsequent observation by the subjects.

Step 2: Show the sample images to the subjects and ask them to divide the sample images into two categories based on their preferences: liking and disliking. This study invited 18 experts to conduct one-on-one interviews online or offline for approximately 30 to 60 min on the collected sample images. The respondents consist of 9 males and nine females, aged between 24 and 38, with 13 aged between 24 and 29 and 5 aged between 30 and 39. Regarding professional background and work experience, there are six design graduate students, six design teachers each, 4 product designers, and two mechanical designers. All participants have more than five years of industrial design experience. The detailed background information of the subjects is shown in Table 1.

Step 3: Inquire about the specific reasons why the subjects like the sample images and determine the key reason why the sample attracts users, which is the original evaluation layer (middle layer). At the beginning of the experiment, participants conducted detailed comparisons of wheelchair samples. They conducted in-depth interviews on their strengths, weaknesses, personal preferences, and other aspects to obtain preliminary reasons for product preferences. During the interview process, participants can remove samples of wheelchair products they do not like to ensure that the remaining samples can more accurately reflect their preferences.

Step 4: Conduct in-depth interviews with the subjects regarding their preferences for a specific sample using the EGM method. This step aims to obtain the upper-level abstract emotional preferences, middle-level original design items of specific attractiveness, and lower-level specific design elements triggered by the sample from the subjects.

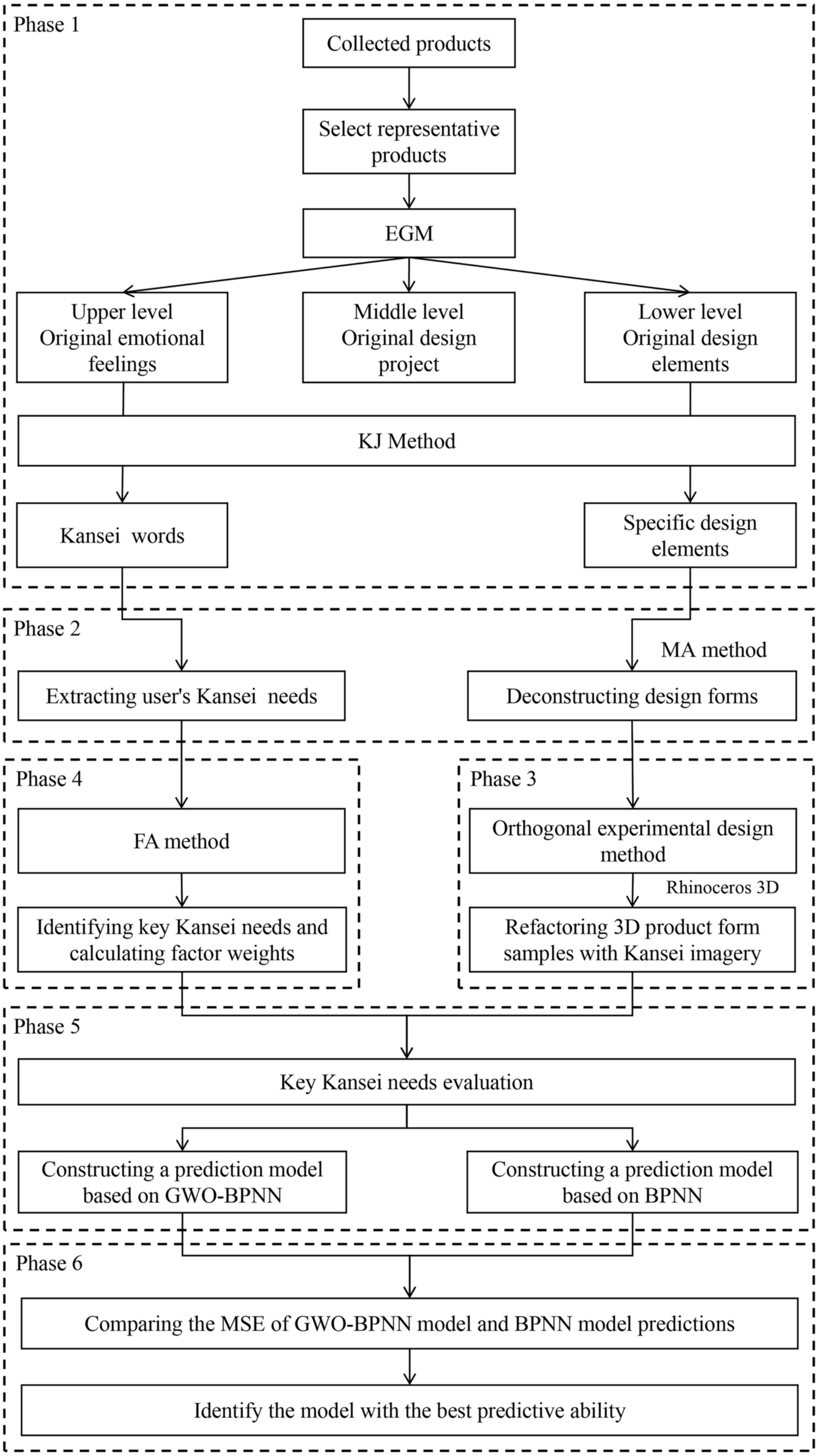


Fig. 3. Research flowchart.

Step 5: Construct a hierarchical relationship grid diagram between emotional adjectives and styling design elements. Based on the experimental results of the upper, middle, and lower evaluation items and the correlation between each level, an individual evaluation structure relationship grid diagram was drawn and saved as a document.

Fig. 4. 35 wheelchair samples.

Project	Content	Number
Gender	Male	9
	Female sex	9
Age	24–29	13
	30–38	5
Profession	Design graduate students	6
	Design professional teacher	6
	Product designer	4
	Mechanical designer	2

Table 1. Subject information.

Step 6: Use the KJ simplification method[73] to merge identical or similar attribute items; repeat this step until no further grouping is possible to obtain apparent attractiveness factors for the product. The number of interview project results collected through EGM experiments is vast. Specifically, there are 1918 upper-level evaluation projects, 1210 middle-level evaluation projects, and 312 lower-level evaluation projects. This study uses the KJ method to combine and simplify similar Kansei factors and design features to avoid burdening designers with too many attractive factors during the analysis process. After this step, the attractiveness factors were finally obtained, with 15 evaluation items at the upper level, nine at the middle level, and 26 at the lower level.

This series of refined evaluation projects has formed an attractive wheelchair product hierarchy logic diagram, thereby establishing a complete evaluation system and forming an evaluation grid diagram, as shown in Fig. 5.

Extraction of affective words

According to the frequency of positive adjectives mentioned by participants in personal interviews with EGM, 15 upper-level abstract Kansei adjectives are included. Kansei words and their frequencies are shown in Table

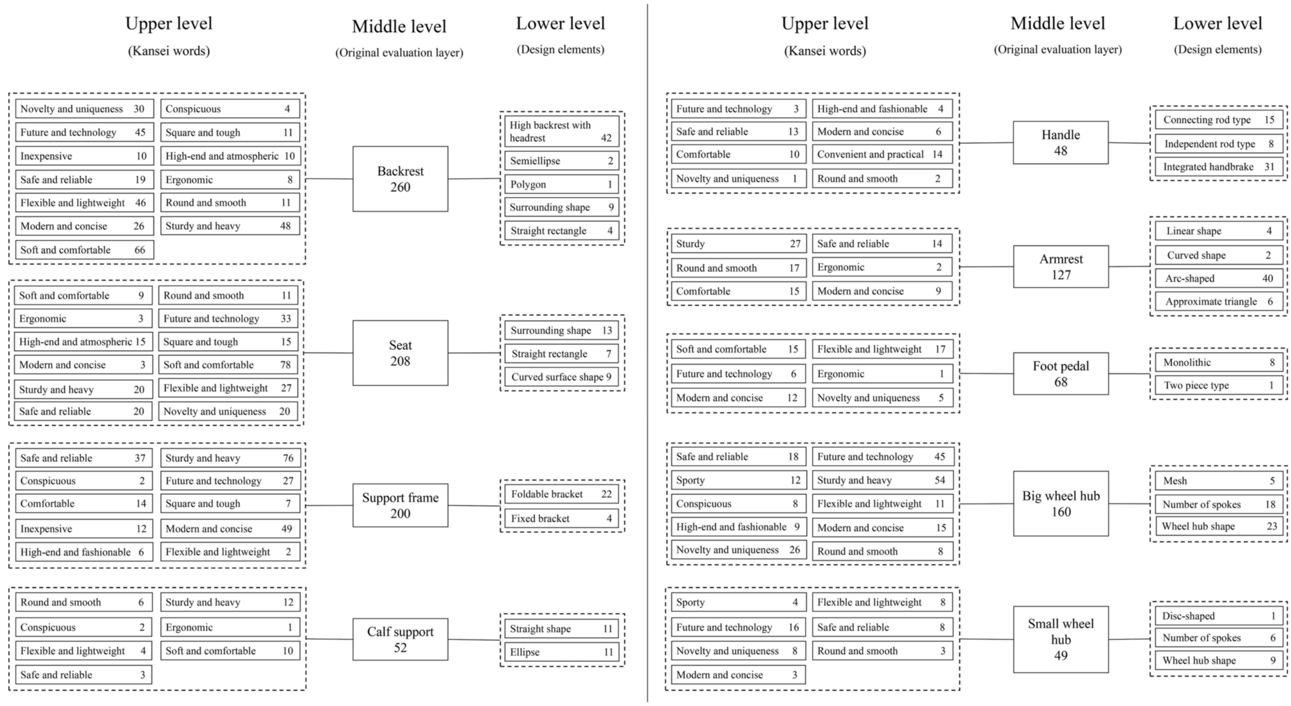


Fig. 5. Evaluation grid chart.

Kansei words	Frequency	Kansei words	Frequency	Kansei words	Frequency
Sturdy and heavy	237	Flexible and lightweight	115	Square and tough	33
Soft and comfortable	208	Novel and unique	90	Affordable	22
Futuristic and technological	160	Convenient and practical	60	Conspicuous	16
Safe and reliable	134	Smooth and rounded	58	Sporty	16
Modern and concise	133	High-end and fashionable	34	Ergonomic	14

Table 2. Kansei words.

Number	1	2	3
Kansei words	Technological–Ordinary	Comfortable–Uncomfortable	Safe–Dangerous
Number	4	5	6
Kansei words	Sturdy–Fragile	Concise–Complex	Round–Square
Number	7	8	9
Kansei words	Modern–Traditional	Affordable–Expensive	Lightweight–Heavy

Table 3. Nine pairs of Kansei words with positive and negative poles.

2. Based on the frequency of participants' mentions, the nine most essential evaluation items were selected and paired into nine sets of Kansei word pairs through antonyms, as shown in Table 3.

To alleviate the cognitive load on participants in the next stage of SD evaluation and to prioritize the user's Kansei needs in wheelchair form design. The SD method and FA method were used to determine the emotional needs of each user and the factor weights in the user's emotional rating to identify critical emotional needs. Firstly, nine sets of Kansei word pairs were combined with 35 wheelchair samples to construct the Likert-7 scale, which ranges from −3 to 3, specifically: −3, −2, −1, 0, 1, 2, 3. In the scale, emotional words are placed on the left and right sides of the scale, and participants can score each wheelchair sample based on their subjective preferences. If the score tends towards a negative value, it indicates that the sample is more in line with the description of the left adjective (-3 is the most suitable). Conversely, if the score tends towards a positive value, it indicates that the sample is more in line with the description of the correct adjective (3 is the most suitable). Choosing 0 suggests that the subject holds a neutral attitude. The fifty-six participants were invited to participate in the SD assessment, including 32 males (average age of 28.38 years) and 24 females (average age of 26.96 years).

By statistically processing the Kansei evaluation data of 35 wheelchair samples, the average value of each sample under each Kansei word pair was obtained. The specific statistical results are shown in Table 4.

Then, using the maximum variance method, exploratory FA is conducted through factor rotation to extract factors with eigenvalues threshold more significant than 1. Before performing dimensionality reduction on the ratings of 9 emotional word pairs, it is necessary to conduct KMO and Bartlett sphericity tests on the applicability of FA. The value of KMO is 0.712 (KMO > 0.6), and the significance P-value of Bartlett's sphericity test is 0.000***($P < 0.05$), indicating that there is a correlation between the variables and FA can be performed. Table 5 shows the total variance explanation of the Kansei factors, with three components having eigenvalues more significant than one and a cumulative contribution rate of 87.521%. The results indicate that the nine Kansei factors can be reduced to three main factors, which have good explanatory power for the appearance design elements of wheelchairs. In addition, to ensure the reliability of the statistical data obtained, we also conducted a reliability analysis on the questionnaire. Cronbach's α value is an essential indicator for measuring the reliability of a questionnaire. The analysis results show that the Cronbach's α value is 0.981. According to Taber[74], a Cronbach's α value of 0.7 indicates the questionnaire's satisfactory reliability or internal consistency. Therefore, the questionnaire results of this study demonstrate reasonable reliability.

The Kansei factors were orthogonally rotated using the Caesar normalization maximum variance method, and the rotated factor loading coefficients are shown in Table 6. Positive numbers indicate positive correlations between indicators, while negative numbers indicate negative correlations between indicators. In this study, users' Kansei needs can be met by categorizing all Kansei words into three main types.

Sample	Round–Square	Technological–Ordinary	Modern–Traditional	Concise–Complex	Lightweight–Heavy	Comfortable–Uncomfortable	Safe–Dangerous	Sturdy–Fragile	Affordable–Expensive
Y1	0.246	0.895	0.351	0.842	0.965	−0.175	−0.351	−0.281	0.140
Y2	0.211	−0.211	−0.439	−0.719	−0.035	−0.316	−0.175	−0.632	0.000
Y3	1.825	0.789	0.491	0.298	0.175	0.825	0.439	0.211	−0.281
Y4	1.456	0.737	0.456	0.825	0.807	−0.140	−0.333	−0.561	0.386
Y5	−0.281	−0.368	−0.386	−0.421	−0.228	0.368	0.421	−0.175	1.000
Y6	1.281	1.632	1.474	0.070	−0.544	−0.088	−0.105	0.228	−0.456
Y7	1.298	0.544	0.035	0.140	0.018	−0.140	−0.509	−0.702	0.246
Y8	0.228	0.193	−0.035	−0.088	0.281	−0.088	0.246	−0.351	1.526
Y9	−0.526	−0.456	−0.632	−0.158	0.439	−0.368	−0.123	−0.596	1.088
Y10	0.544	0.491	0.140	0.123	−0.368	−0.298	−0.684	−0.263	−0.351
Y11	1.333	0.789	0.491	0.000	0.000	−0.018	−0.526	−0.246	−0.316
Y12	0.107	0.018	−0.143	0.250	−0.036	1.232	1.357	0.875	0.982
Y13	−0.175	−0.649	−0.491	−0.526	0.158	−0.263	−0.246	−0.404	1.053
Y14	0.088	−0.298	−0.456	0.614	0.912	−0.228	−0.544	−0.316	0.947
Y15	0.965	−0.263	−0.368	−0.386	0.018	−0.386	−0.456	−0.474	0.526
Y16	−0.140	−0.211	−0.421	−0.158	0.439	0.211	0.333	−0.579	0.877
Y17	0.228	−0.526	−0.439	−0.421	−0.228	0.421	0.702	−0.368	0.789
Y18	0.754	0.298	0.193	0.930	0.579	−0.579	−0.649	−0.649	0.298
Y19	−0.140	−0.351	−0.368	−0.281	0.404	−0.246	0.211	−0.228	0.596
Y20	0.772	−0.211	−0.579	−0.456	−0.316	−0.333	0.000	−0.368	0.421
Y21	1.193	0.386	0.281	0.193	−0.158	−0.211	−0.596	−0.088	−0.070
Y22	0.807	0.140	0.123	0.491	0.421	−0.474	−0.368	−0.614	0.088
Y23	0.123	−0.474	−0.474	−0.579	−0.175	−0.544	−0.544	−0.596	0.456
Y24	−0.193	−0.228	−0.421	−0.193	0.702	0.263	0.351	−0.298	1.018
Y25	0.754	0.579	0.386	0.368	0.123	−0.298	−0.333	−0.211	0.053
Y26	0.807	0.228	0.018	−0.316	−0.070	0.368	−0.105	−0.070	−0.228
Y27	0.281	−0.281	−0.351	1.649	0.912	0.351	−0.123	−0.333	0.789
Y28	−0.614	−0.526	−0.614	−0.702	0.263	−0.053	−0.140	−0.561	0.982
Y29	0.860	0.474	0.456	−0.298	−0.053	0.053	−0.351	−0.351	0.140
Y30	1.000	0.316	0.333	0.298	0.456	−0.491	−0.684	−0.561	0.246
Y31	0.702	−0.246	−0.632	1.263	1.246	−0.316	−0.211	−0.316	0.877
Y32	1.211	0.772	0.439	−0.474	−0.386	0.018	−0.281	0.263	−0.404
Y33	0.807	0.526	0.333	0.386	0.000	−0.316	−0.404	−0.456	−0.193
Y34	0.737	0.491	0.491	−0.088	−0.140	−0.123	−0.228	0.018	−0.333
Y35	0.825	0.702	0.491	−0.351	−0.456	−0.105	−0.211	0.035	−0.175

Table 4. Average score matrix of Kansei evaluation for 35 wheelchair samples.

Component	Explanation rate of variance before rotation			Explanation rate of variance after rotation		
	Eigenvalue	Variance explanation rate (%)	Cumulative variance explanation rate (%)	Eigenvalue	Variance explanation rate (%)	Cumulative variance explanation rate (%)
1	3.765	41.834	41.834	374.537	41.615	41.615
2	2.482	27.581	69.416	238.346	26.483	68.098
3	1.629	18.105	87.521	174.808	19.423	87.521
4	0.358	3.977	91.498			
5	0.291	3.236	94.734			
6	0.19	2.108	96.842			
7	0.138	1.538	98.381			
8	0.108	1.194	99.575			
9	0.038	0.425	100			

Table 5. Explanation of total variance.

Kansei words	Factor load coefficient after rotation			Kansei factors	Factor weight (%)
	Factor 1	Factor 2	Factor 3		
Round–Square	0.868	− 0.060	0.077	Modern and technological	47.549
Technological–Ordinary	0.949	0.070	0.060		
Modern–Traditional	0.939	0.074	− 0.014		
Comfortable–Uncomfortable	− 0.031	0.943	0.016	Safe and comfortable	30.259
Safe–Dangerous	− 0.361	0.878	− 0.084		
Sturdy–Fragile	0.373	0.816	− 0.129		
Concise–Complex	0.246	− 0.013	0.930	Lightweight and concise	22.192
Lightweight–Heavy	− 0.337	− 0.146	0.887		
Affordable–Expensive	− 0.875	0.149	0.251		

Table 6. Factor load factor table.

The first factor consists of three indicators: "round–square," "technological–ordinary," and "modern–traditional." It is named "modern and technological" factor and has a maximum weight of 47.549%. This factor reflects that users prefer wheelchairs with modern technological design styles.

The second factor consists of "comfortable–uncomfortable," "safe–dangerous," and "sturdy–fragile," and is named "safe and comfortable" factor with a weight of 30.259%. This factor indicates that users have higher requirements for the safety and comfort of wheelchair use.

The third factor consists of "concise–complex," "lightweight–heavy," and "affordable–expensive," and is named "lightweight and concise" factor with a weight of 22.192%. This factor indicates that users desire a wheelchair with a simple design that saves time and effort and is convenient.

Based on the above factor analysis results, three critical quality characteristics that affect users' emotional perception of wheelchair form were determined, namely modern technology sense, safety and comfort sense, and lightweight and concise sense, as the critical Kansei demand factors for wheelchair form design elements.

Deconstruction of design elements

While conducting interviews with experts using EGM, this study extracted the mid-level primary attractiveness factors, namely the reasons why users like the product, as critical components. In addition, based on the specific design elements of the lower layer shown in the evaluation grid Fig. 5, a systematic deconstruction of the appearance characteristics of the wheelchair was carried out using the morphological analysis method. The appearance hierarchy of the product design was deeply analyzed, and the corresponding relationship between the wheelchair product shape design and the original attraction factors was explored. According to the wheelchair product design system in this article, the morphological analysis method decomposes the wheelchair form into the following nine main parts: seat, backrest, support frame, armrest, big wheel hub, small wheel hub, handle, calf support, and foot pedal. Each section is subdivided into multiple design categories for more detailed analysis and comparison. Based on the aesthetic characteristics analysis of 35 wheelchair products, corresponding design element hierarchy categories were obtained. Furthermore, Auto CAD software was used to draw the design elements into 2D shapes, and the specific experimental results are shown in Table 7. It includes nine design features and 36 design categories and is coded.

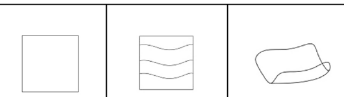
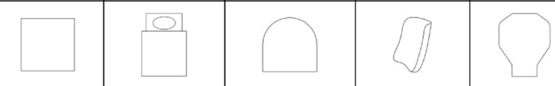
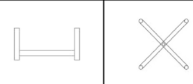
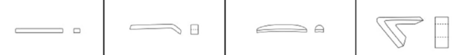
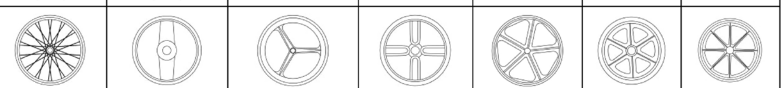
Product features	Category						
Seat (X1)							
	Straight rectangle (C11)	Curved surface shape (C12)	Surrounding shape (C13)				
Backrest (X2)							
	Straight rectangle (C21)	High backrest with headrest (C22)	Semi ellipse (C23)	Surrounding shape (C24)	Polygonal (C25)		
Support frame (X3)							
	Fixed bracket (C31)	Foldable bracket (C32)					
Armrest (X4)					None		
	Linear shape (C41)	Curved shape (C42)	Arc-shaped (C43)	Approximate triangle (C44)	No armrests (C45)		
Handle (X5)				None			
	Connecting rod type (C51)	Independent rod type (C52)	Integrated handbrake (C53)	No handle (C54)			
Foot pedal (X6)							
	Monolithic (C61)	Two piece type (C62)					
Big wheel hub (X7)							
	Multi spoke hub (C71)	Two spoke hub (C72)	Three spoke hub (C73)	Four spoke hub (C74)	Five spoke hub (C75)	Six spoke hub (C76)	Eight spoke hub (C77)
Calf support (X8)			None				
	Straight shape (C81)	Ellipse (C82)	Legless support (C83)				
Small wheel hub (X9)							
	Disc-shaped hub (C91)	Three spoke hub (C92)	Four spoke hub (C93)	Five spoke hub (C94)	Six spoke hub (C95)		

Table 7. Design element categories (2D shapes).

Construction of product concept schemes

The design categories are decomposed based on the qualitative analysis of product form elements. In each design feature, only one design category is selected for arrangement and combination to reconstruct experimental survey samples and expand the survey from the sample library. In addition to the previously selected representative samples, a total of 126,000 ($3\times5\times2\times5\times4\times2\times7\times3\times5$) new wheelchair shape combinations were obtained by cross-combining the samples, thereby expanding and reconstructing the product shape sample library. However, in the experimental design, consideration was given to the cognitive redundancy of individuals regarding the existence of information. If a large amount of sample information is used for questionnaire surveys, it may lead to poor reliability and validity due to information overload. An orthogonal experiment (OE) design method was adopted to ensure the representativeness of the experimental group and avoid this problem[75]. However, this OE design belongs to several nonequal levels and cannot be directly used in the experimental table. According to the feature and category classification in Tables 7 and 9 product features are set as nine factors, and the number of categories for each feature is set as several corresponding nonequal level distributions. Sixteen experimental samples are extracted using the OE method. Using SPSSAU online analysis software, generate an OE plan table for feature and category data, as shown in Table 8.

Based on the shape contours of each design category, 2D shapes were first drawn using Auto CAD models (Table 7). Subsequently, using computer-aided technology, the 2D shapes were converted into 3D shapes using Rhinoceros 3D design modelling software, and the 3D model effects of the design categories are shown in Table 9.

Furthermore, based on the 16 design category combination schemes in Table 8 of the OE plan, a complete 3D product conceptual model was constructed using Rhinoceros 3D design modeling software, and the 3D model was rendered using Keyshot software to complete the conceptual scheme for creating the wheelchair. For example, the design category combination of Scheme 1 is C11, C21, C32, C41, C53, C62, C71, C81, and C94. Based on the shape and functional layout of the wheelchair, a frame structure model of the wheelchair is constructed using steel pipes, and each design element is placed in the corresponding position of the wheelchair frame to build the conceptual scheme of the wheelchair. Similarly, the other 15 wheelchair concept schemes were constructed in the same way, resulting in 16 wheelchair concept schemes, as shown in Fig. 6. These 16 schemes will be the objects of SD evaluation in the next stage.

Construction of mapping model

Establishing a mapping model between user emotional imagery and product form features is the core of KE, but the relationship between the two is often highly nonlinear. BPNN is a mature machine learning technique that can effectively fit this mapping relationship and achieve prediction of user emotional perception. In addition, to enhance the predictive performance of BPNN, this study introduces the GWO algorithm into BPNN. Through multiple iterations of the GWO algorithm, the global optimal weights and thresholds were obtained, and the weights and thresholds of BPNN were optimized to improve the gradient information of BPNN and shorten the error. This study compared the performance of two algorithm models, BPNN and GWO-BPNN, and selected the better emotion prediction model. Select mean squared error (MSE) and mean relative error (MBE) as indicators to evaluate the model's performance. The construction process of the GWO-BPNN prediction model is shown in Fig. 7. In addition, the general steps of the GWO algorithm are as follows:

Step 1: Normalize the sample data using Eq. (12).

$$\mathrm{x}_{\alpha} = \frac{\mathrm{X}_{\alpha} - \mathrm{X}_{\min}}{\mathrm{X}_{\max} - \mathrm{X}_{\min}} \tag{12}$$

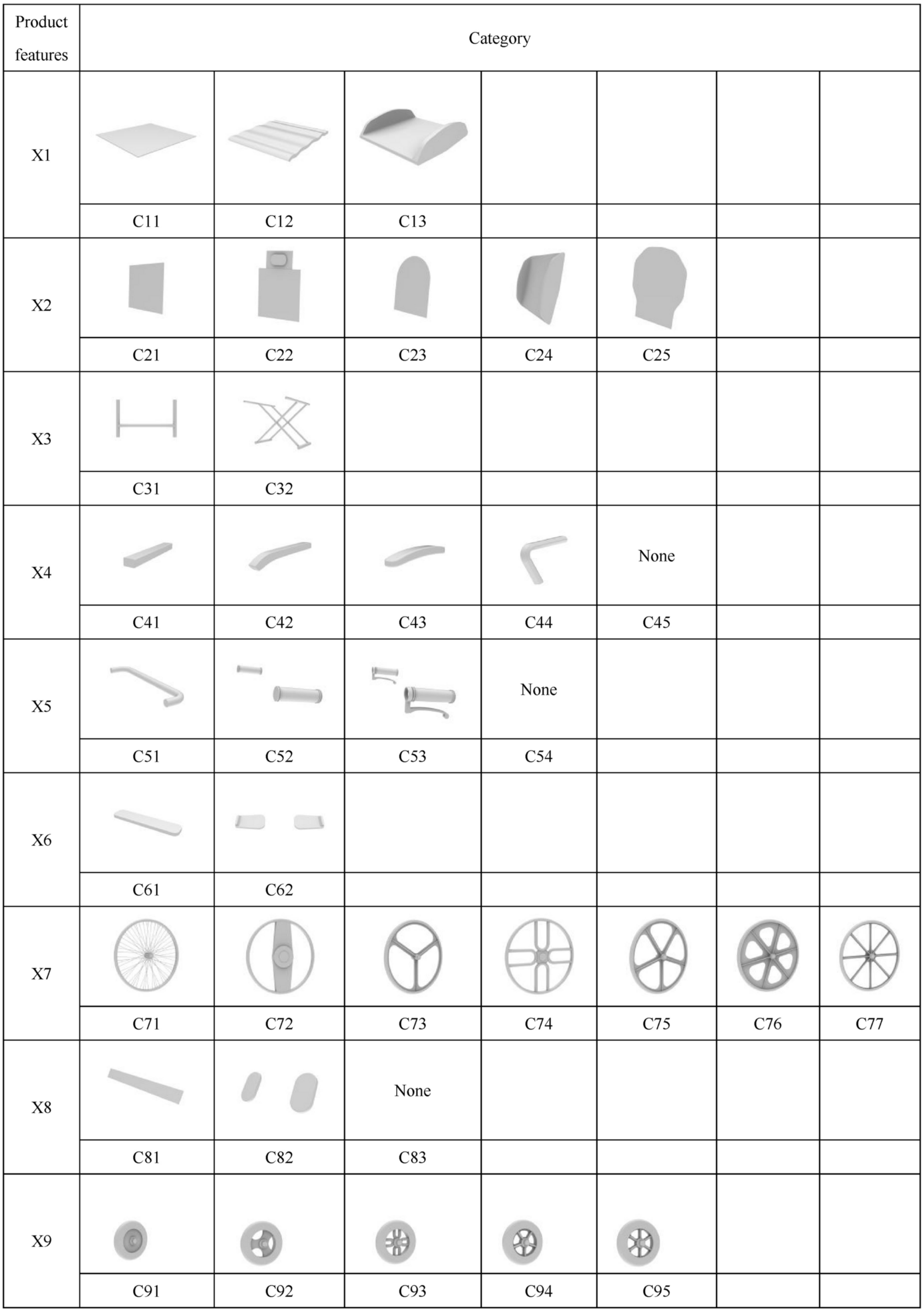
Among them, X_{max} represents the maximum value in the original data, X_{min} represents the minimum value in the original data, and X_{α} represents the normalized data.

Step 2: Build a BPNN and use Eq. (13) to calculate the number of hidden layer neural nodes.

$$\mathrm{H} = \sqrt{\mathrm{M} + \mathrm{N}} + \mathrm{a} \tag{13}$$

Scheme	X1	X2	X3	X4	X5	X6	X7	X7	X9
F1	C11	C21	C32	C41	C53	C62	C71	C81	C94
F2	C13	C25	C31	C45	C54	C61	C74	C83	C93
F3	C12	C21	C32	C43	C53	C62	C71	C81	C92
F4	C12	C21	C31	C41	C53	C62	C73	C83	C92
F5	C11	C21	C32	C43	C53	C62	C75	C82	C94
F6	C12	C22	C31	C43	C52	C62	C75	C83	C95
F7	C12	C24	C31	C45	C51	C62	C73	C83	C91
F8	C11	C21	C32	C42	C53	C61	C73	C82	C91
F9	C11	C21	C32	C41	C51	C61	C75	C83	C95
F10	C13	C21	C32	C41	C51	C61	C75	C83	C95
F11	C11	C25	C32	C42	C51	C61	C75	C83	C91
F12	C11	C25	C32	C42	C51	C61	C72	C83	C95
F13	C11	C23	C32	C41	C54	C61	C75	C83	C91
F14	C12	C25	C32	C43	C51	C62	C75	C82	C94
F15	C12	C23	C32	C41	C51	C61	C75	C82	C94
F16	C12	C25	C31	C45	C51	C61	C72	C82	C94

Table 8. Orthogonal experiment plan.



Product features	Category						
X1	C11	C12	C13				
X2	C21	C22	C23	C24	C25		
X3	C31	C32					
X4	C41	C42	C43	C44	None C45		
X5	C51	C52	C53	None C54			
X6	C61	C62					
X7	C71	C72	C73	C74	C75	C76	C77
X8	C81	C82	None C83				
X9	C91	C92	C93	C94	C95		

Table 9. Design Element Categories (3D Shapes).

Among them, H is the number of hidden layer nodes, M is the number of input layer nodes (number of design features), N is the number of output layer nodes (number of Kansei words), and a is an integer between 0 and 10.

Step 3: Initialize GWO parameters. Determine the size of the grey wolf population, maximum iteration times, dimensions and upper and lower bounds of the grey wolf individual position information, and randomly initialize the grey wolf position.

Step 4: Calculate the fitness value of individuals, set the weights and thresholds of BPNN as the optimization objects of the GWO algorithm, use the total error of each neuron node of BPNN as the fitness function of the

Fig. 6. 16 wheelchair concept schemes.

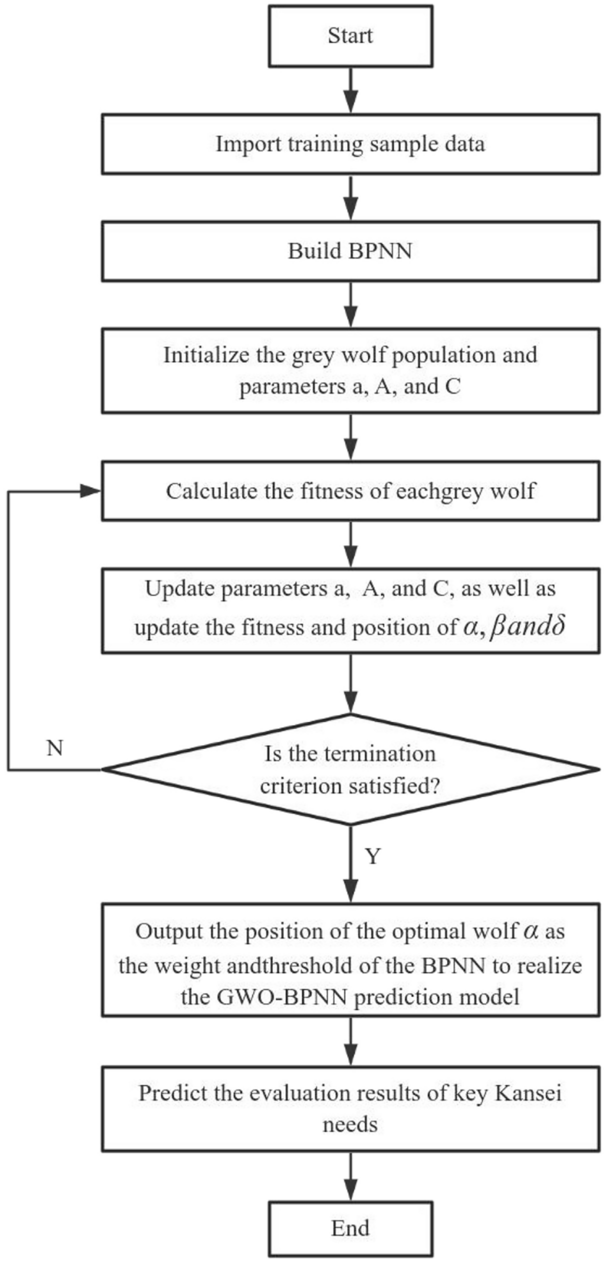


Fig. 7. Construction process of GWO-BPNN prediction model.

GWO optimization algorithm, measure the quality of individual positions, and obtain the current position with the best fitness value.

Step 5: Determine whether the maximum number of iterations has been reached. When the number of iterations reaches the upper limit, the GWO optimization algorithm ends and finally obtains the optimal initial weights and thresholds for BPNN.

Step 6: Output the position of the optimal wolf α and map it to the weight matrix, which serves as the weight from the hidden layer to the output layer of the BPNN, to implement the GWO-BPNN model.

Step 7: Preprocess the test sample data, input it into the trained GWO-BPNN model, obtain the predicted results, and compare them with the actual values to verify the model's reliability.

Evaluation of key Kansei needs

Firstly, use Keyshot software to display all wheelchair concept schemes in Fig. 6 by dynamically rotating the wheelchair models of each scheme 360 degrees around the Z-axis of the model, with the model center as the origin, for 5 s, and rendering them as 3D dynamic videos. Then, using the SD method, the 3D dynamic videos of 16 wheelchair concept schemes were combined with three key Kansei needs to design a key Kansei needs evaluation questionnaire for wheelchair representative samples. Invite 84 participants (42 males and 42 females, aged between 18 and 49 years) to rate the critical Kansei needs of 16 3D dynamic video wheelchair concept plans in three categories: "modern and technological," "safe and comfortable," and "lightweight and concise." Participants can click multiple times to play the video for easy observation of the shape of the wheelchair concept plan. Taking "modern and technological" as an example, the evaluation scale is set to 1 to 7 points, where 1 point indicates that the sense of modern and technological style is not apparent, 2 points suggest that it is somewhat obvious, 3 points indicate that it is more prominent, 4 points suggest that it is pretty evident, 5 points indicate that it is pronounced, 6 points suggest that it is pronounced, and 7 points indicate that it is pronounced.

The critical Kansei needs evaluation steps for this stage are as follows: The first step is for the subjects to fill in their personal information. Step 2: Play the 3D dynamic video of each wheelchair concept scheme and watch the overall 3D form effect of the scheme, as shown in Fig. 8. Take a screenshot of the 3D dynamic video of the scheme. The third step is to rate the three Kansei needs of the wheelchair concept plan being viewed. Repeat steps two and three until the evaluation of 16 wheelchair concept schemes is completed.

After completing the data collection, calculate the average score of each solution on the Kansei requirements. Then, combining the factor weights of essential Kansei needs, a weighted calculation is performed to obtain each scheme's comprehensive Kansei evaluation value, as shown in Table 10. The highest comprehensive Kansei evaluation value for Plan 14 is 5.13, and the lowest is 3.946 for Plan 1. Through analysis, it can be found that conceptual scheme 14 has the best combination of shape optimization design categories, specifically including curved rectangular seats, polygonal backrests, foldable support frames, curved armrests, connecting rod type handles, two piece type foot pedals, five-spoke large wheel hubs, elliptical calf supports, and five-spoke small wheel hubs.

Establishment of prediction model based on GWO-BPNN

Encode the morphological features of 16 wheelchair concept schemes, critical Kansei demand scores, and comprehensive Kansei evaluation values, and integrate them into a wheelchair morphological Kansei evaluation matrix, as shown in Table 10. Based on the Matlab R2022a software platform, the morphological features of 16 wheelchair concept schemes were encoded as independent variables, and the comprehensive Kansei evaluation value was used as the dependent variable, which was input into the GWO-BPNN model for training. Randomly select 12 out of 16 samples as the training set and the remaining four schemes as the testing set. During the training process, the training frequency is set to 1000, the learning rate to 0.01, and the minimum training error value to 0.000001. Using the formula (13), determine the appropriate number of hidden layer nodes to be 15 (MSE = 0.017526). After initializing the weights and thresholds of BPNN, use the GWO algorithm to initialize the objective function values of α, β, and δ, and use formulas (1–11) to calculate fitness and update the positions of α, β, and δ. The population size is set to 200. Finally, the position of the optimal wolf α is output, and the weight matrix is mapped to optimize the weights and thresholds of the BPNN, achieving the construction of

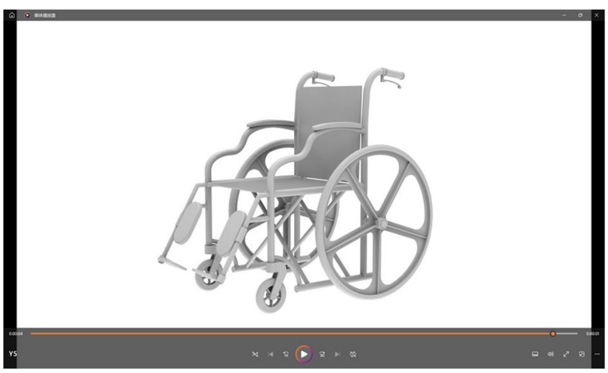


Fig. 8. Screenshot of 3D dynamic video of sample.

Sample	Wheelchair morphological feature encoding	Modern and technological	Safe and comfortable	Lightweight and concise	Comprehensive Kansei evaluation value
F1	100,100,000,110,000,010,011,000,010,000,010	3.583	4.012	4.631	3.946
F2	001,000,011,000,010,001,100,001,000,100,100	4.821	3.869	5.202	4.618
F3	010,100,000,100,100,010,011,000,010,001,000	4.833	5.167	5.155	5.006
F4	010,100,001,010,000,010,010,010,000,101,000	4.274	4.226	5.310	4.489
F5	100,100,000,100,100,010,010,000,101,000,010	4.488	5.167	4.571	4.712
F6	010,010,001,000,100,100,010,000,100,100,001	4.357	4.619	5.024	4.584
F7	010,000,101,000,011,000,010,010,000,110,000	4.452	4.226	5.369	4.587
F8	100,100,000,101,000,010,100,010,001,010,000	4.512	5.036	4.738	4.721
F9	100,100,000,110,001,000,100,000,100,100,001	3.583	4.512	5.512	4.292
F10	001,100,000,110,001,000,100,000,100,100,001	5.048	5.024	5.202	5.075
F11	100,000,010,101,001,000,100,000,100,110,000	4.429	4.607	5.095	4.205
F12	100,000,010,101,001,000,100,100,000,100,001	4.345	4.726	5.214	4.355
F13	100,001,000,110,000,001,100,000,100,110,000	4.702	5.274	4.940	4.641
F14	010,000,010,100,101,000,010,000,101,000,010	5.095	5.036	5.333	5.130
F15	010,001,000,110,001,000,100,000,101,000,010	4.429	4.798	5.012	4.670
F16	010,000,011,000,011,000,100,100,001,000,010	4.381	4.738	5.036	4.634

Table 10. Kansei evaluation matrix for wheelchair form.

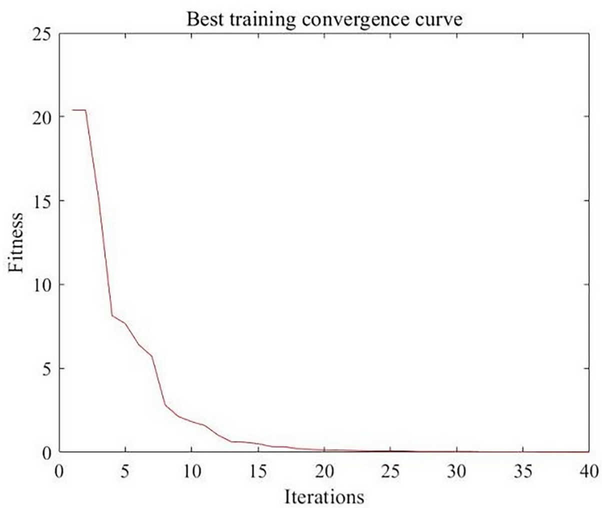


Fig. 9. GWO-BPNN training results.

the GWO-BPNN model. Figure 9 shows where GWO-BPNN reaches its lowest fitness level after 40 training sessions. The comparison curve between the predicted results of the training set and the actual values is shown in Fig. 10. The comparison curve between the predicted results of the test set and the actual values is shown in Fig. 11. The predicted values, actual values, MSE values, and MBE values (MSE = 0.0329, MBE = 0.0334) of the test set are shown in Table 11, indicating that the GWO-BPNN model has an excellent fitting effect on the test set.

Comparison of prediction models

The data from Table 10 was used and inputted into BPNN for training. Randomly select 12 out of 16 samples as the training set and the remaining four schemes as the testing set. During the training process, the training frequency is set to 1000, the learning rate to 0.01, and the minimum training error value to 0.000001. In this study, the number of nodes in the input layer corresponds to 33 key design elements, and the number of nodes in the output layer is 1. According to formula (13), the appropriate number of hidden layer nodes is determined by selecting the minimum mean square error, ultimately resulting in 12 (MSE = 0.0253) nodes. The hidden and output layers use the Logsig and Purelin functions, respectively. The model is trained using the Trainlm gradient descent function. After multiple iterations, the model achieved good convergence on the training set. The comparison curve between the predicted results of the training set and the actual values is shown in Fig. 12. The comparison curve between the predicted results of the test set and the actual values is shown in Fig. 13. The

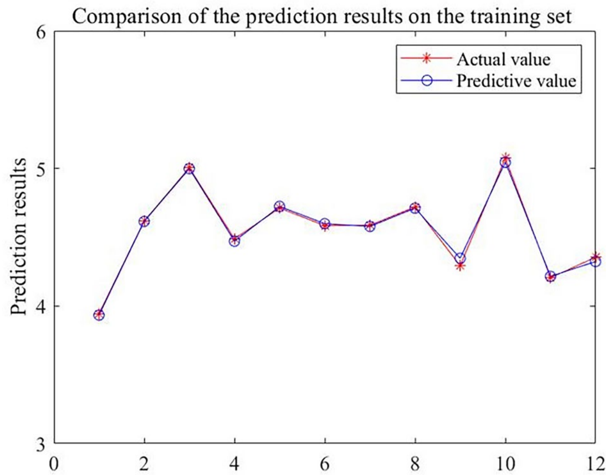


Fig. 10. Prediction results of GWO-BPNN training set.

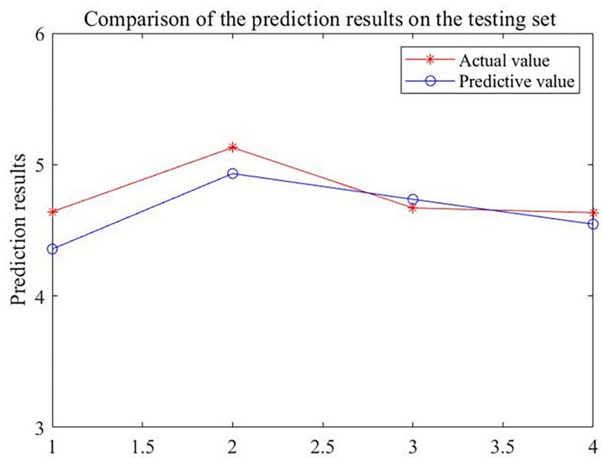


Fig. 11. Prediction results of GWO-BPNN test set.

Network architecture	Test1		Test2		Test3		Test4		MBE	MSE
	Predictive value	Actual value	Predictive value	Actual value	Predictive value	Actual value	Predictive value	Actual value		
BPNN	5.1129	4.5843	5.0527	5.0748	4.8412	5.1301	4.5673	4.4892	0.0739	0.0923
GWO-BPNN	4.3578	4.6410	4.9318	5.1301	4.7355	4.6697	4.5469	4.6343	0.0334	0.0329

Table 11. Comparative analysis of model prediction results for the test set.

predicted values, actual values, MSE values, and MBE values (MSE = 0.0923, MBE = 0.0739) of the test set are shown in Table 11. The fitting effect of the test model is good.

This study selected a three-layer structure network with hidden layers. Among them, 33 design elements are the network's input layer, and the comprehensive Kansei evaluation value is the output layer. Train the network using BPNN and GWO-BPNN algorithms. Moreover, the prediction results will be analyzed using the comprehensive Kansei evaluation values of four test samples, and the error values of the two prediction models on the test set (Table 11) will be compared to identify the model with the highest predictive ability. According to the error values in Table 11, the MSE of the BPNN model is 0.0923, while the GWO-BPNN model is 0.0329, significantly better than the BPNN model. The results indicate that the GWO-BPNN model better predicts the comprehensive Kansei evaluation value of wheelchair shape design than the BPNN model. The results suggest that the GWO-BPNN model better predicts the comprehensive Kansei evaluation value of wheelchair shape design.

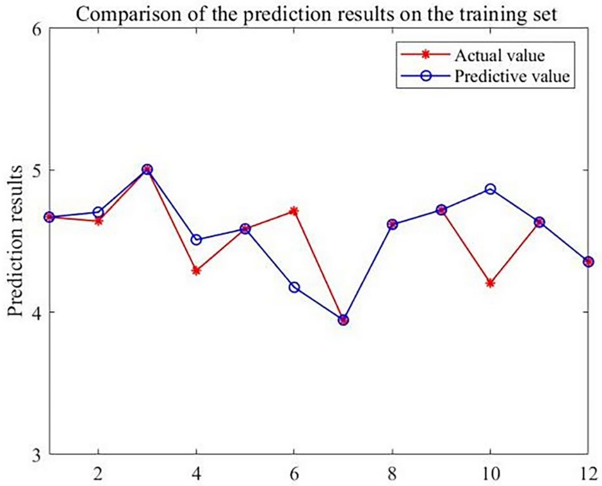


Fig. 12. Prediction results of BPNN training set.

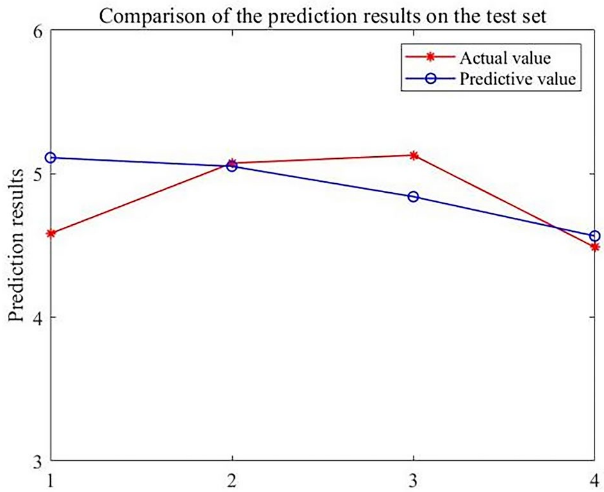


Fig. 13. Prediction results of BPNN testing set.

Discussion

Looking back at previous studies, most focused on studying consumers' functional needs for wheelchairs, and few studies explored the relationship between specific design elements of wheelchairs and consumers' emotional needs. Therefore, this study applies the Kansei Engineering (KE) to the field of wheelchair design, identifying and simulating consumers' emotional reactions to explore their emotional preferences for wheelchair design in order to better guide wheelchair design.

Accurately identifying consumers' emotional needs is crucial in the research of KE. EGM is an effective Miryoku Engineering research method that can effectively identify consumers' perceived attractiveness of products in ambiguous information conversations. This study utilized EGM expert interviews to extract 3440 original attraction factors for wheelchairs. To simplify the analysis process and avoid the burden of too many attractive factors on designers, the KJ method merged and simplified similar factors, resulting in 15 upper-level evaluation items, nine middle-level evaluation items, and 26 lower-level evaluation items. A user attractiveness-centered evaluation grid diagram was constructed. This process not only helps us identify the core emotional needs of consumers for wheelchair design but also provides a foundation for extracting design elements in the future. On this basis, based on the frequency of participants' mentions, nine upper-level abstract emotions were selected as the most important factors influencing consumers' purchase of products, and nine sets of emotional word pairs were constructed as evaluation carriers through the antonym pairing method. Then, to alleviate the cognitive load on participants in the subsequent SD assessment. Through factor analysis, three critical emotional needs factors and their weights were extracted, namely "modern and technological" (47.549%), "safe and comfortable" (30.259%), and "lightweight and concise" (22.192%). These factors can attract consumers' attention and reflect their aesthetic and functional needs for wheelchair form design. Therefore, consumers usually hope that the design of the wheelchair form has a more technological sense. In addition, while ensuring safety, it is convenient to use and travel and provides a certain level of comfort.

The extraction of product design elements is the key to further analyzing the characteristics of wheelchair design elements. This study utilized the morphological analysis to identify nine design projects and 36 specific design elements were identified from the middle and lower-level projects extracted by EGM (Table 7). By cross-combining design elements, 126,000 new wheelchair shape combinations were obtained to reconstruct the product shape sample library. Considering that information overload may affect the reliability and validity of the questionnaire, an orthogonal experimental (OE) design was used to obtain 16 proposals. The OE design method has strong screening ability and can select potentially attractive design combinations from a large number of design possibilities. In most cases, the Kansei evaluation of a product involves finished product images rather than actual products or conceptual models. To give users a more comprehensive understanding of the product form design category combination scheme, we used computer-aided technology Rhinoceros 3D design modeling software to transform design category combinations from 2D shapes to 3D conceptual models, forming 16 new 3D form wheelchair concept schemes (see Fig. 6), and constructing 16 representative 3D dynamic videos of the samples. Furthermore, by using a 3D dynamic video display, a 3D conceptual model of the product was provided for users to observe from multiple perspectives, overcoming the limitations of previous research on product form based solely on a single perspective of two-dimensional images, allowing consumers to have a more comprehensive and intuitive understanding of the form of the solution. This not only improves the intuitiveness of the design but also enables consumers to have a more comprehensive understanding of the design intent. we transformed the design category combination from 2D shapes to 3D conceptual models, forming a new 16 3D form wheelchair concept schemes (see Fig. 6).

In the Kansei evaluation stage, 3D dynamic videos are used to display the product form, user Kansei evaluation data is collected, and factor weights are used to calculate each representative sample's comprehensive Kansei evaluation value. The results showed that the comprehensive Kansei evaluation value of representative scheme 14 was the highest (5.13). The design category combination of this sample is a curved rectangular seats, polygonal backrests, foldable support frames, curved armrests, connecting rod type handles, two piece type foot pedals, five-spoke large wheel hubs, elliptical calf supports, and five-spoke small wheel hubs. Therefore, designers can focus on the attractiveness factors of consumer preferences based on research results and plan development strategies for new products.

Finally, using the Kansei evaluation results, BPNN and GWO-BPNN models will be trained to construct the mapping relationship between design elements and critical Kansei requirement evaluations. The data in Table 11 shows that the MBE of the BPNN model is 0.0739. The MBE of the GWO-BPNN model is 0.0334. The results indicate that the GWO-BPNN model has lower MBE in prediction, suggesting that the GWO-BPNN model has better predictive ability. The GWO-BPNN technique performs well on the dataset used in this study and demonstrates excellent results in different datasets and research questions. For example, in emotional design, Chen and Cheng[55] used GWO-BPNN to evaluate the relationship between paper-cutting pattern design elements and consumer perception. In their model, the design element data of paper-cutting patterns are taken as input variables, and the perception evaluation data of perception adjectives are taken as output variables. By comparing and analyzing the BPNN model and FA-BPNN model, the accuracy of the proposed GWO-BPNN model is tested. The results indicate that the GWO-BPNN model provides more accurate predictions than the BPNN and FA-BPNN models. Uzlu[76] used GWO-ANN technology in energy policy to predict Türkiye's future energy consumption. The model prediction results indicated that the GWO-ANN model has significant advantages in predictive ability compared to traditional BP-ANN and ABC-ANN models. Uzlu[35] used the GWO-ANN model to predict Türkiye's future greenhouse gas emissions in environmentally sustainable development. The research results shown that the GWO-ANN model outperforms the BP-ANN, ABC-ANN, and TLBO-ANN models in terms of performance. The results obtained from different datasets and problems are consistent with the findings of this study, further confirming that GWO-BPNN technology is a method with high predictive ability and reliability. The results indicate that the method proposed in this study can help designers apply and combine wheelchair form design elements according to the perceived needs of different consumers, provide targeted design solutions for users, improve design efficiency and consumer satisfaction, and provide scientific support for personalized design and application of wheelchairs.

However, although the GWO-BPNN model has demonstrated strong optimization capabilities in multiple fields, it also has some limitations that may affect its application effectiveness in areas such as wheelchair design. For example, the training method of BPNN based on gradient descent may lead to it falling into local minima rather than global optima, which is particularly evident in complex problems[55]. Although the GWO algorithm optimizes the weights and biases of BPNN, improving convergence speed, it is still necessary to consider how to reasonably set the parameters of GWO to avoid premature convergence or low search efficiency[35]. Due to the multiple iterations and training of multiple models involved in the GWO-BPNN model, there is a high demand for computing resources, which may limit its application in resource-constrained environments[76]. NN models are often considered "black box" models, and their decision-making process lacks transparency[77]. In certain fields, such as medical diagnosis or financial risk assessment, the interpretability of the model is crucial, which may be a limitation of the GWO-BPNN model. In summary, although the GWO-BPNN model has shown potential in multiple fields, it still needs to overcome these limitations in practical applications. Therefore, future research can explore more advanced optimization algorithms and ensemble learning methods to further improve prediction accuracy and model generalization ability and applicability. Through these efforts, we aim to enhance the effectiveness and reliability of the GWO-BPNN model in applications such as wheelchair design. In addition, Wang and Pei[78] demonstrated in their research the powerful capabilities of Interactive Evolutionary Computation (IEC) algorithms in solving many real-world problems. Especially in the field of product design research, IEC provides a favorable design environment for product development. Interactive Genetic Algorithm

(IGA) is a classic method in IEC[78]. IGA allows users to directly participate in product design activities, integrate their emotional needs into product design, and flexibly adjust product design features by designing interactive interfaces to generate high-quality solutions for users[4]. Therefore, in future research, we consider combining IGA with user emotional preferences to further develop an automatic wheelchair design system that generates customized wheelchairs based on user preferences and designs high-satisfaction wheelchair products with users at the center.

Conclusion

This study proposes an innovative wheelchair form design method that integrates EGM and GWO-BPNN based on the theory of KE. This method not only expands wheelchair design's user needs but also delves deeper into users' emotional needs, providing industrial designers with a new design perspective. Firstly, this study utilized the EGM expert interview method to obtain the attractiveness factors of users towards wheelchair product design. Then, using morphological analysis and orthogonal experimental design methods and utilizing computer-aided technology Rhinoceros 3D design modeling software, a wheelchair conceptual scheme was constructed, and a 3D dynamic video of the conceptual scheme was produced as the evaluation object. On this basis, a Kansei evaluation was conducted to determine the design category combination of the conceptual scheme with the highest comprehensive Kansei evaluation value. Finally, a predictive model for key Kansei requirements was established using BPNN and GWO-BPNN, and a mapping relationship between design elements and key Kansei factors was constructed to enhance the attractiveness of wheelchair design. The comparative analysis with the BPNN prediction model reveals that the GWO-BPNN model, with its smaller prediction error and better prediction performance, validates the superiority and practicality of the model. The method proposed in this study can help designers more comprehensively and accurately grasp users' emotional needs and create wheelchair designs that meet both functional requirements and emotional appeal, thereby enhancing user experience and satisfaction. This study not only provides a new design strategy for wheelchair form design but also contributes a new perspective to research and practice in product design. Nevertheless, this study still has certain limitations.

(1) Research on wheelchair products is complex and may involve factors such as engineering mechanics. This study focuses on exploring the factors of product form design, but factors such as material, colour, functionality, and human–machine interaction also influence consumers' decision-making. Future research will continue to explore the impact of other product factors on user emotional preferences.
(2) Converting 2D shapes of design categories into 3D shapes and constructing 3D conceptual models and dynamic videos is slow and requires much time and effort. In future research, computer-aided technology can construct a parametric design platform that parameterizes 2D shapes and generates 3D shapes by controlling their parameters, reducing the burden on personnel.
(3) In this study, the GWO algorithm was used to optimize the BPNN model, but the results may not be optimal in all cases. Therefore, more comparative research on intelligent algorithms is necessary to improve prediction efficiency and results.

In summary, the method proposed in this study was applied to a wheelchair form design case, verifying its effectiveness and feasibility and emphasizing the importance of incorporating emotional design elements into wheelchair design. With the advancement of technology and the continuous development of design theory, the method proposed in this study is expected to be further optimized and improved, providing more robust support for product design innovation.

Data availability

The data used to support the findings of this study are included in the manuscript.

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Author contributions
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Declarations

Competing interests
The authors declare no competing interests.

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